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Detection the Impact of Chlorophyll Index and Global Environmental Monitoring Index on Water Separation in Swansea in Wales, United Kingdom Through Analysing the Spectral Wavelengths of Landsat 8-OLI

Hayder H. Kareem[1*], Zainab Ali Omran[2], Muammar H. Attaee[3]

[1] Structures and Water Resources Engineering Department, Faculty of Engineering, University of Kufa, Al-Najaf, Iraq
[2] Department of Civil Engineering, Faculty of Engineering, University of Babylon, Babylon, Iraq
[3] Department of Civil Engineering, College of Engineering, University of Misan, Misan, Amarah 62001, Iraq
* Corresponding author's e-mail: hayderh.alshaibani@uokufa.edu.iq

ABSTRACT

Understanding the condition, spatial arrangement, and changing patterns of vegetation cover holds significant scientific and economic importance. Satellite platforms offer a highly convenient means to study how vegetation reacts to atmospheric influences by gauging reflectance in the visible and near-infrared spectra. Given the numerous potential origins of environmental land cover variability, this study seeks to examine how vegetation cover influences water separation. This is achieved by identifying the chlorophyll index (CIG) and global environmental monitoring index (GEMI) to enhance the vital safeguarding of water sector against the encroachment of excessive vegetation. To gain deeper insights into the impact of extensive vegetated areas, we have analyzed the CIG and GEMI within Swansea County, situated in Wales, United Kingdom. These emphasized indices are applied and their effectiveness is evaluated using geographic information systems and remote sensing technology. The outcomes of the CIG and GEMI analyses reveal that the indexes exhibit their lowest and highest values at (-1.38) and (1.75105, -9.61413e+008) respectively. These findings indicate the presence of extensive vegetated regions with a substantial proportion of chlorophyll emissions being reflected into the atmosphere. The dispersion of chlorophyll concentrations across the environment implies a significant risk to the water sector, potentially resulting in severe shortages and the potential for future water scarcity. Elevated readings of the CIG and GEMI indicate extensive coverage of Earth's surface by vegetation, impacting the crucial water resources essential humanity. It is prudent to safeguard freshwater reserves and utilize it wisely to maintain its permanence.

Keywords: GIS, remote sensing technology, CIG, GEMI, Swansea, United Kingdom.

INTRODUCTION

The chlorophyll index (CI) or chlorophyll index green (CIG) is a critical parameter in plant science and remote sensing (RS) that quantifies the relative chlorophyll content in vegetation. Chlorophyll, the green pigment vital for plant photosynthesis, acts as a crucial indicator of plant vitality and well-being. The chlorophyll index is determined by examining how plant leaves either reflect or absorb light at specific wavelengths (Anatoly et al., 2002). Remote sensing technologies, such as satellites and drones, have significantly transformed our capacity to observe and evaluate vegetation across extensive areas. The utilization of the chlorophyll index proves indispensable in remote sensing applications as it empowers researchers and land managers to gain valuable insights into the status and effectiveness of plant ecosystems (Penuelas et al., 1995). Determining CIG often involves evaluating the reflectance of light at specific wavelengths, notably the red (R) and near-infrared (NIR) bands. RS tools are frequently employed in this process to collect data from the Earth's surface.

By analyzing the reflectance values in these bands, scientists can derive the chlorophyll index, providing information about chlorophyll concentration and indirectly indicating the health and stress levels of plants. The CIG aids in comprehending the dynamics and well-being of plant ecosystems by assessing and overseeing them in diverse environments (Nathalie et al., 2009).

The global environmental monitoring index (GEMI) stands as a critical framework employed in environmental studies and policy to assess and quantify the worldwide state of environmental well-being and sustainability. GEMI offers a comprehensive and standardized method for tracking pivotal environmental indicators, enabling researchers, policymakers, and stakeholders to appraise the overall state of the planet and monitor advancements toward sustainable development goals, aligned with directives from the United Nations Environment Programme (2002) and the Millennium Ecosystem Assessment (2005). Covering an extensive range of environmental factors, GEMI encompasses elements from air and water quality to biodiversity and markers of climate change. This inclusive approach permits a holistic appraisal of the Earth's ecosystems and their interconnectedness. By consolidating data and metrics from diverse sources, GEMI provides a unified platform for scrutinizing environmental patterns and identifying areas necessitating attention and intervention (World Health Organization, 2016). The creation and implementation of GEMI involve cooperative endeavors among scientists, organizations, and governments globally. This index serves as a valuable instrument for prioritizing environmental initiatives, guiding policy choices, and encouraging worldwide collaboration in addressing urgent environmental challenges. GEMI continues to hold a significant role in shaping our comprehension of global environmental circumstances and steering endeavors towards a more sustainable and resilient future (Intergovernmental Panel on Climate Change, 2014).

Numerous studies have demonstrated that the fraction of photosynthetically active radiation that is absorbed can be effectively extracted using two primary approaches. One approach involves employing vegetation indices (VIs) within a statistical model (Gitelson et al., 2014; Ogutu et al., 2014). The second approach involves utilizing the inversion of a canopy reflectance model (Frédéric et al., 2007; Verger et al., 2011, Dong et al., 2012). Among these methods, the utilization of VIs is more prevalent compared to the inversion of canopy reflectance models. These VIs primarily rely on mathematical functions utilizing visible and near-infrared reflectance (NIR) data to uncover the photosynthetic capacity of the canopy. The visible reflectance component captures the chlorophyll content, signifying the greenness, while the NIR reflectance component captures attributes related to canopy structure, such as leaf angle distribution (Pinty et al., 2009; Viña et al., 2011). Recently, chlorophyll-related VIs, especially those centered on the red-edge reflectance, have gained prominence for estimating leaf or canopy chlorophyll content (Haboudane et al., 2008; Wu et al., 2008; Delegido et al., 2011; Peng et al., 2011; Hunt et al., 2013). Notable examples include the transformed chlorophyll absorption in reflectance index to optimized soil-adjusted vegetation index ratio (TCARI/OSAVI) (Daughtry et al., 2000) and the modified chlorophyll absorption ratio index (MCARI) to OSAVI ratio (MCARI/OSAVI) (Zarco-Tejada et al., 2004), both of which have demonstrated sensitivity to leaf chlorophyll content. Understanding the numerical significance of these indices presents a challenge due to their considerable sensitivity to various factors. These factors include the atmospheric conditions and the angles of illumination and observation. In the context of global monitoring endeavors, where the goal is to describe the Earth's surface through the examination of the spatial or temporal patterns of these indices, it is assumed that, except in cloudy regions, alterations in surface characteristics are responsible for the observed variations, rather than shifts in atmospheric circumstances (Holben and Fraser, 1984; Holben, 1986; Holben et al., 1986; Lee and Kaufman, 1986).

The science of remote sensing has developed to be characterized by its high and accurate ability to monitor various environmental changes in addition to the changes experienced by the climate, as it has become a powerful and very effective tool in detecting terrestrial changes. Through remote sensing technology, scientists and researchers have been able to collect various data from a remote place using different and diverse sensors, such as self-piloted aircraft that do not require a pilot, satellites, and various ground devices linked to remote sensing technology. This advanced technique and technology has greatly improved the ability to understand and see the various dynamic processes that occur across time and space on the surface of the Earth (Duy et al., 2023).

Environmental sciences have developed widely based on remote sensing technology, as this technology has been able to collect various data related to the Earth's surface or atmosphere without direct human contact, collecting that data in addition to analyzing it accurately and extracting the information hidden in it. This technology is distinguished by its high-capacity electromagnetic radiation, which contains a wide range of wavelengths, which makes it capable of having a profound impact on transformative technologies for deducing various variables, as it has been able to monitor natural environmental events in addition to those events resulting from human interactions on the surface of the Earth. Remote sensing technology is represented by obtaining data and spectral images with multiple wavelengths, which gives it the ability to detect and supervise changes that occur in the land cover, the atmosphere, and even the interior of the earth, through which human activities on the surface of the earth, change in vegetation cover, can be monitored. Population and urban expansion, water quality, and changes occurring in forests in an accurate and systematic manner that can be analyzed scientifically and its results can be relied upon. In respect of climate change studies, RS provides critical information about shifts in the Earth's climate system. It facilitates the monitoring of temperature variations, sea level rise, glacial retreat, and changes in greenhouse gas concentrations. With the ability to observe remote and challenging-to-access regions, RS contributes to a comprehensive understanding of the complex interactions driving climate change and its consequences (Blaga et al., 2023).

Occasionally, the extensive vegetation cover can lead to a reduction in soil moisture levels, exacerbating the demand for irrigation water and further amplifying the already pressing requirement for water in an environment marked by severe scarcity of water. Consequently, due to the lack of studies specifically addressing the CIG and GEMI and their relationship with water sector, this study lays the foundation for enhancing and maintaining verdant vegetation within the worldwide ecosystem. It achieves this by employing RS and geospatial methods (such as ArcGIS) to assess the CIG and GEMI using Landsat 8 imagery within a designated region of interest, Swansea County in Wales in the United Kingdom, to assess the impact of these indexes on the reduction of water that will separate from land surface cover.

Swansea region of interest

Swansea, situated on the coast, holds the position of being Wales' second-largest city. It constitutes a key administrative region known officially as the County of Swansea. In the United Kingdom, it ranks as the twenty-fifth largest city. Positioned by Swansea Bay in the southwestern part of Wales, the primary area encompasses the Gower Peninsula, thus becoming an integral component of both the Swansea Bay locale and the historical Glamorgan county. Additionally, it is rooted in the ancient Welsh commote of Gŵyr. With an estimated populace of 246,563 in 2020, Swansea stands as the second most densely inhabited local governing body in Wales. Swansea has a population about 300,352 in 2011. Furthermore, it plays a significant role within the Swansea Bay City Region (Largest Cities in the UK, 2017).

Swansea exhibits division into four distinct physical regions, each characterized by intricate geological formations that contribute to its diverse and captivating landscapes. Notably, the Gower Peninsula holds the distinction of being the first location in the United Kingdom to attain the prestigious status of an Area of Outstanding Natural Beauty (AONB), encompassing the entirety of the peninsula except for its southeastern corner. Swansea boasts a multitude of both urban and rural parklands, a fact that has led to consistent recognition in the Wales in Bloom awards. Swansea's topography is predominantly undulating, with notable elevations occurring within the Mawr council ward. The central portion of the city features elevation fluctuations of up to 185 meters. This central area is demarcated by prominent geographical features such as Kilvey Hill, Townhill, and Llwynmawr, which serve to delineate the core of Swansea from its northern suburban areas (Student information – Swansea geography, 2007).

Swansea experiences a warm and temperate climate, characterized by consistent rainfall even during the least wet months. This climate falls under the Cfb classification (warm temperate, fully humid, with warm summers) according to the Köppen and Geiger system. The annual average temperature in Swansea measures 13.1 °C, accompanied by an annual precipitation of approximately 587 mm. Situated in the southern hemisphere, the summer season spans from the end of January through December, encompassing the months of December, January, February, and

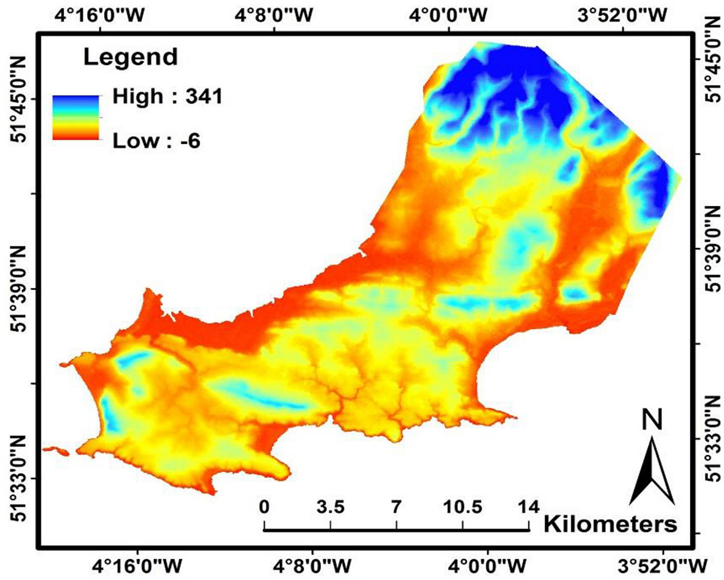


Figure 1. DEM of Swansea

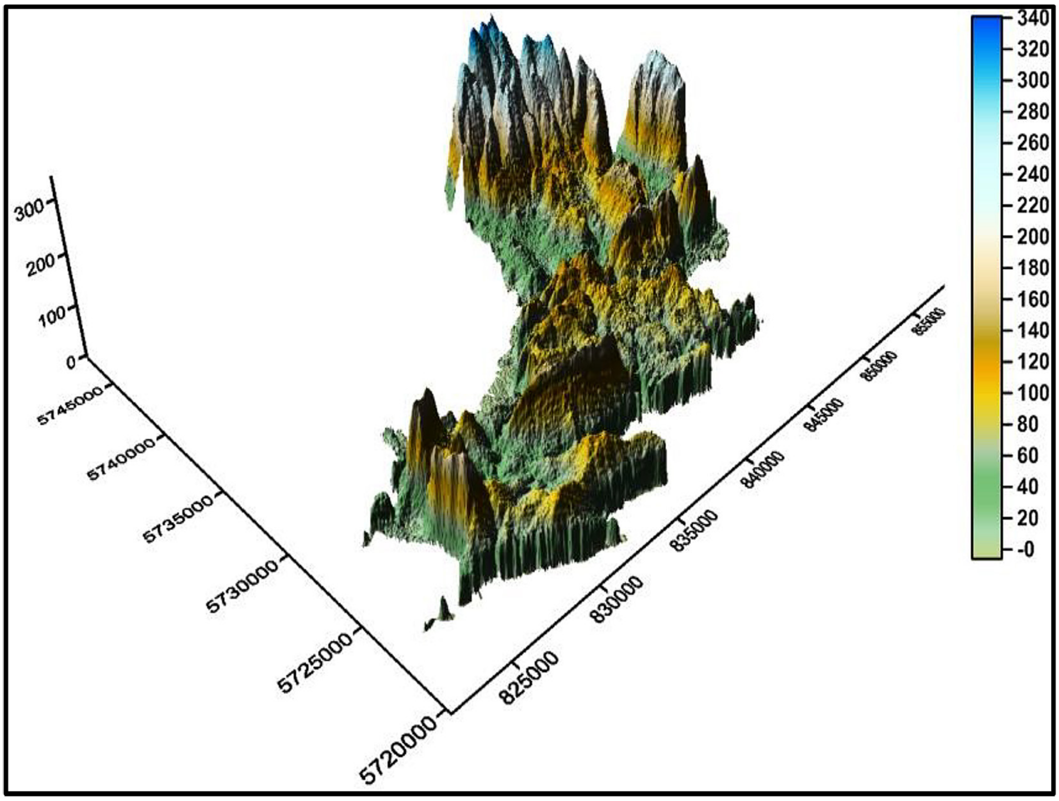


Figure 2. 3-Dimensional sketch showing the ground surface levels of Swansea

March. Notably, June exhibits the highest relative humidity at 76.91%, whereas December records the lowest relative humidity at 65.24%. In terms of precipitation, November stands as the wettest month, while May is the driest (Peel et al., 2007; UK climate extremes, 2023). Figs. 1 and 2 demonstrate the downloaded digital elevation model (DEM) of Swansea and a 3-dimentioal sketch of the ground surface elevations, respectively.

CIG and GEMI fundamental description

The CIG is a RS-derived parameter used to assess the chlorophyll content and health of vegetation. CIG is extracted through the vegetation that reflects more green light and less near-infrared light due to the absorption of red and blue light for photosynthesis. The CIG provides valuable insights into plant health, stress, and chlorophyll concentration, which in turn can indicate factors like nutrient deficiencies, water stress, and overall vegetation vitality. This information is particularly useful for precision agriculture, crop monitoring, and environmental assessments. The CIG is often calculated using various bands of satellite or airborne RS data. Eq. (1) is the only one common formula to calculate CI or CIG is (Gitelson et al., 1996):

$$CIG = \frac{Band5}{Band3} - 1 \tag{1}$$

where: *Band3* – the reflectance of green wavelength of Landsat 8-OLI. *Band5* – the reflectance of near infrared wavelength of Landsat 8-OLI.

Incorporating environmental monitoring should be a fundamental component within a country's biodiversity management framework, serving as a key resource to educate both decision makers and the general population. National systems for monitoring biodiversity (referred to as NBMSs) ought to emphasize the evaluation of stressors, influential elements, and policy actions using defined indicators. The efficacy of these NBMSs hinges upon the degree to which biodiversity indicators are directly aligned with officially stated national objectives concerning the preservation of biodiversity and the responsible utilization of natural resources. The GEMI approach constitutes a nonlinear vegetation index utilized in worldwide environmental surveillance via satellite images. While akin to NDVI, it demonstrates reduced susceptibility to atmospheric influences. It does respond to exposed soil, thus making it unsuitable for application in regions characterized by limited or moderately concentrated vegetation. The GEMI can be estimated using Eqs. (2) and (3) illustrated below (Pinty and Verstraete, 1992).

$$GEMI = ETA * (1 - 0.25 * ETA) - \left(\frac{Band4 - 0.125}{1 - Band4}\right) \tag{2}$$

$$ETA = \frac{(2 * (Band5^2 - Band4^2) + 1.5 * Band5 + 0.5 * Band4)}{(Band5 + Band4 + 0.5)} \tag{3}$$

where: *Band4* – the reflectance of red wavelength of Landsat 8-OLI.

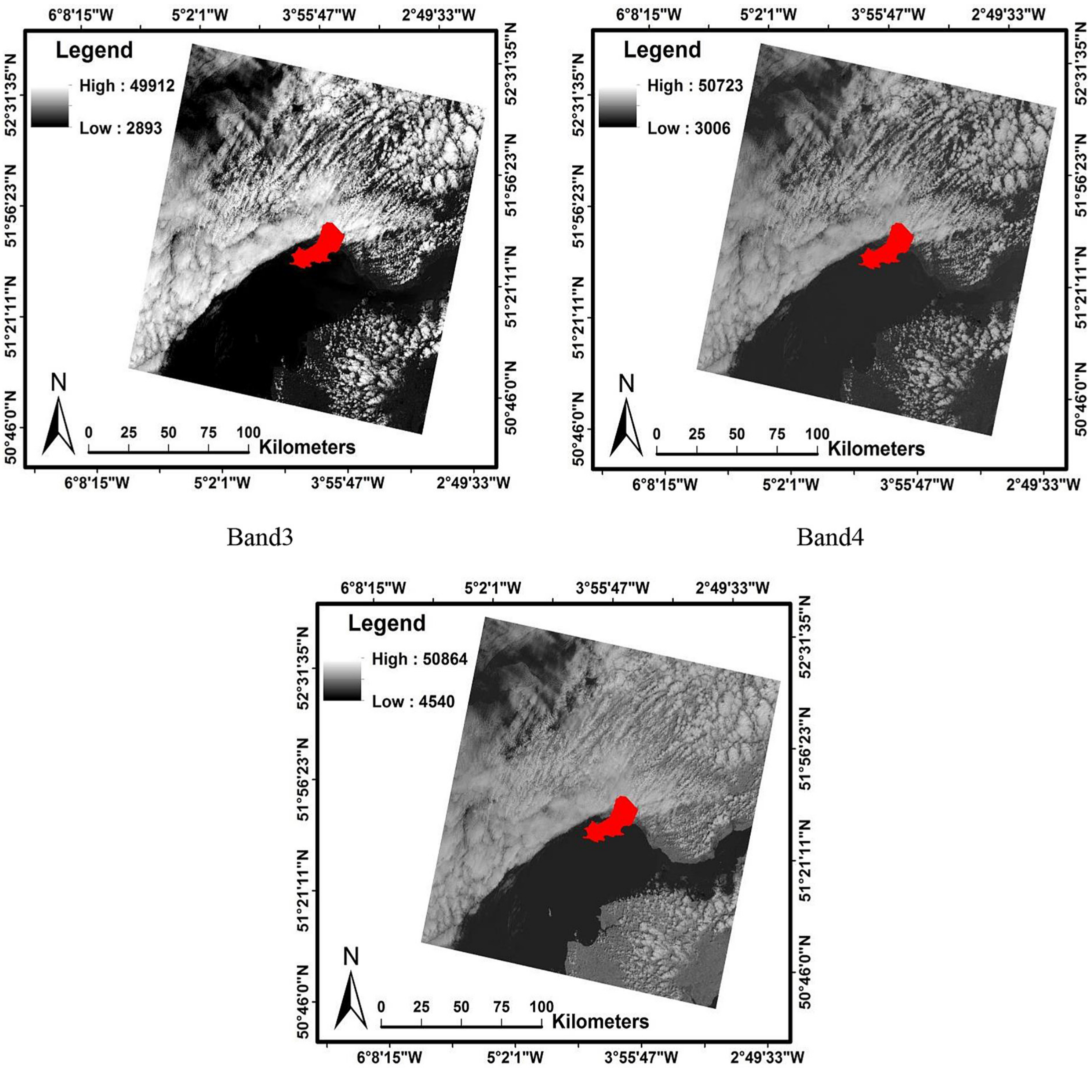
METHODOLOGY

Given the significant advantages of vegetation in contemporary contexts, it is imperative to integrate a precise scientific methodology with geospatial instruments for ascertaining both the condition and geographic scope of vegetation coverage. This preliminary understanding will serve as a foundation for devising forward-thinking tactics concerning land utilization and the stewardship of ecosystems. A pertinent tool poised to lead in gauging the ecological equilibrium of the biosphere via plant monitoring is satellite imagery (Solano-Correa et al., 2018). NASA's recent endeavors encompass the Landsat 8 mission, an orbiting satellite engineered to meticulously map the Earth's terrain and document spatial transformations from its vantage point in space, amassing invaluable RS data. Over four decades after its inception, NASA, in collaboration with the U.S. Geological Survey, introduced the Landsat 8. This satellite holds immense potential in amassing data concerning alterations in the Earth's geographic structure. Its principal objective revolves around Earth observation, tracking alterations across the planet's surface precipitated by both natural processes and human activities. With geographical shifts transpiring at an accelerated pace, scientists aim to closely monitor the Earth's evolving dynamics. Landsat 8 employs the operational land imager (OLI) sensor as a pivotal instrument for data collection, capturing imagery at an impressive spatial resolution of 30 meters (Pettorelli et al., 2014).

Geographic information systems (GIS) and RS stand as formidable and complementary technologies that have transformed the manner in which we amass, dissect, and construe spatial data. These tools wield significant influence in unraveling intricate real-world phenomena, guiding enlightened choices, and tackling an array of environmental and societal predicaments. By amalgamating the analyses of GIS and RS, scholars, policymakers, and experts can delve deeper into comprehending the intricacies of our planet's dynamics, consequently fostering more efficient and substantiated decisions. The inception of GIS tools and methodologies has been instrumental in recognizing, quantifying, and resolving challenges. GIS also offers a forward-looking approach to devising remedies by scrutinizing potential scenarios and initiating preventive strategies. Over time, GIS has enhanced the quality of life for individuals across diverse domains such as telecommunications, events analysis, evaluating environmental impact, estimating flood hazards, managing natural resources, ensuring environmental health and safety, monitoring vegetation, and a myriad of other applications.

This part aims to demonstrate the utilization of meteorology in estimating crucial indicators, namely CIG and GEMI. The Geographic Information System will process the satellite images (captured by Landsat 8) of Swansea in Wales, UK, to derive CIG and GEMI values. Landsat 8 comprises eleven spectral bands. The satellite incorporates the operational land imager (OLI) being linear array systems. The spectral bands of OLI sensor can optimally assess water resources, vegetation cover, coastal regions, and many environmental phenomena. Band 9 of Landsat 8-OLI is designed for the new infrared range, optimized to identify and map areas with cirrus clouds (thin and high) that can obscure clouds, water bodies, and snow.

The downloaded Landsat 8-OLI of Swansea that essential to estimate CIG and GEMI are bands 3, 4, and 5, are illustrated in Figure 3. The highlighted area of interest depicted in Fig. 3 will be processed to extract Bands 3 (green wavelength), 4 (red wavelength) and 5 (near infrared wavelength) of Swansea County. These bands will be then processed to enable the detection of CIG and GEMI. The extensive coverage of the area introduces various challenges, notably concerning reflectivity values, processing time, and effort. Consequently, the GIS program is employed to selectively extract Swansea area of interest, addressing these issues. The outcome of this extraction process is illustrated in Fig. 4.



Band5

Figure 3. Downloaded bands 3, 4, and 5 of Landsat 8-OLI of Swansea

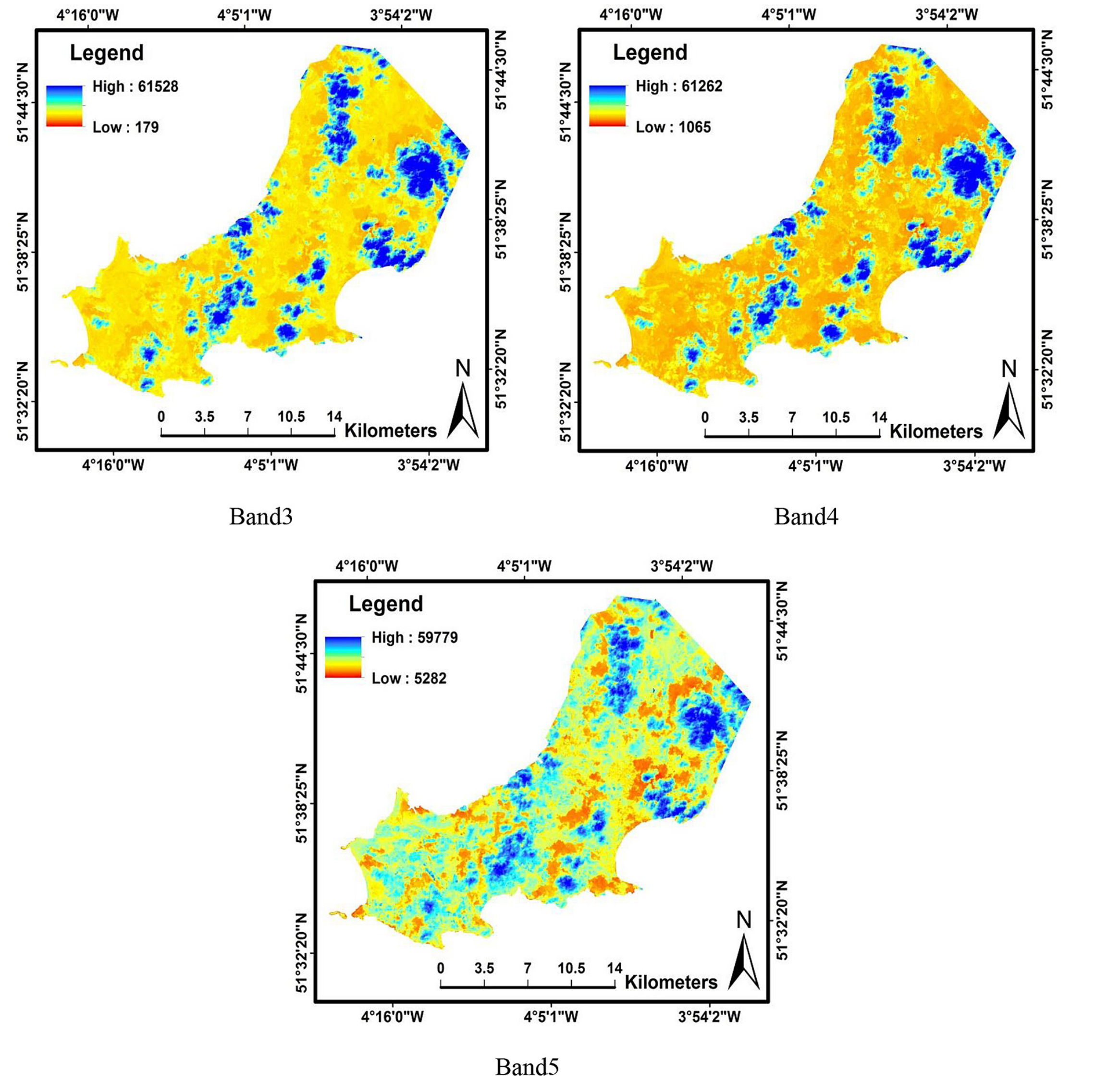


Figure 4. Extracted bands 3, 4, and 5 of Landsat 8-OLI of Swansea

RESULTS AND DISCUSSION

Understanding the condition, spatial arrangement, and changing patterns of vegetation holds significant scientific and economic importance. Satellite platforms offer a highly convenient means of observing the Earth's biosphere on a global scale and with regularity. So far, deriving precise quantitative insights from these observations can pose challenges. Utilizing measurements of reflectance within the visible and near-infrared spectra, straightforward yet effective indices have been developed to amplify distinctions between vegetation and other surface categories. Nonetheless, these indices prove to be quite susceptible to the effect of atmospheric conditions. In recent times, the widespread adoption of GIS and various RS methodologies has resulted in the popularization of applications for processing satellite images. The techniques employed for computing vegetation indices (VIs) and their broad application across diverse landscapes have proven to be highly valuable for the examination of plant life and the analysis of biophysical factors within both forests and agricultural fields. The foundation of VIs in Landsat 8 images is rooted in the selection of combinations of spectral bands that capture surface reflectance across multiple wavelengths. These combinations, either through specific band selections or mathematical formulations, serve to accentuate distinct plant attributes. The specifics of each VI differ based on the methodology employed in its creation and the specific plant feature (such as pigments, water, carbon, chlorophyll, nutrients) being emphasized. Nonetheless, all techniques involving Landsat 8 band combinations rely on the reflective properties exhibited by plants or surface land cover.

Chlorophyll content and global environmental monitoring index values were computed and extensively illustrated in Figs. 5 and 6 for the purpose of comparison. The presence of vegetative cover in various regions was determined using the extracted values of chlorophyll index green and GEMI. Analysis of Landsat 8-OLI images focused on bands 3, 4, and 5, namely green (0.53–0.59), red (0.64–0.67), and near infrared (NIR) (0.85–0.88) bands. Examination of Figure 5 revealed that CIG indicated vegetation chlorophyll levels ranging from -1 to 38, signifying abundant green areas contributing to increased chlorophyll emissions into the atmosphere. Visual assessment of the classification outcomes highlighted GEMI's effectiveness in capturing emission impacts reflected in the atmospheric domain, with values spanning from 1.75105 to -9.61413e+008. Overall, the visual inspection distinctly showcased extensive vegetation coverage, influencing the atmosphere through heightened chlorophyll reflectance into space. These findings have the potential to provide quantitative metrics and visual depictions aiding researchers, policymakers, and stakeholders in making well-informed choices.

In the given paragraph, the chlorophyll index green is specifically mentioned, which likely employs spectral bands sensitive to green light (Band 3 in Landsat imagery). There are practical applications of the chlorophyll Index which can be concluded to: (1) ecosystem health: monitoring changes in chlorophyll content provides insights into the overall health and stress levels of vegetation. Anomalies in chlorophyll levels may indicate nutrient deficiencies, disease, or environmental stressors, enabling timely interventions to mitigate potential risks to ecosystems; (2) crop monitoring and management: for agricultural purposes, chlorophyll indices are used to assess crop health, optimize irrigation, and manage fertilizer application. This helps improve crop yield and resource efficiency; (3) environmental monitoring: monitoring chlorophyll levels in aquatic ecosystems, such as lakes and oceans, offers insights into water quality and algae blooms. Elevated chlorophyll levels may indicate excessive nutrient runoff, potentially leading to eutrophication and ecosystem imbalances; (4) climate change impacts: chlorophyll indices contribute to evaluate land cover changes, and the role of vegetation in mitigating climate change. Changes in chlorophyll content can provide indicators of shifts in ecosystem productivity and dynamics.

In the given paper, GEMI is mentioned as a tool for extracting and quantifying the impact of emissions reflected into the atmosphere, particularly from vegetated areas. The key aspects and implications of the global environmental

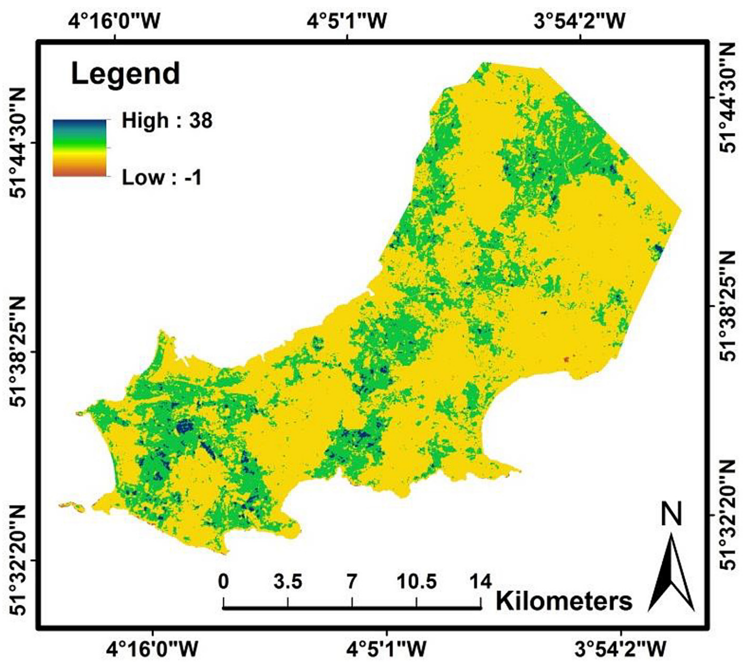
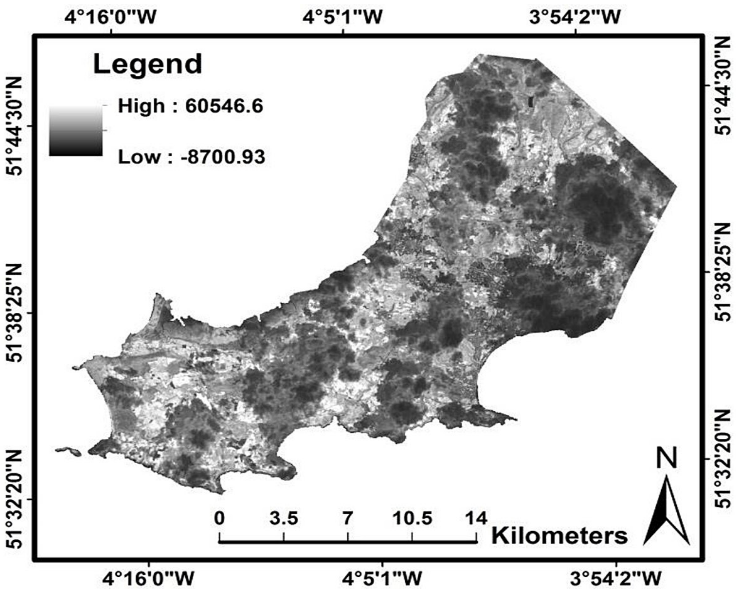
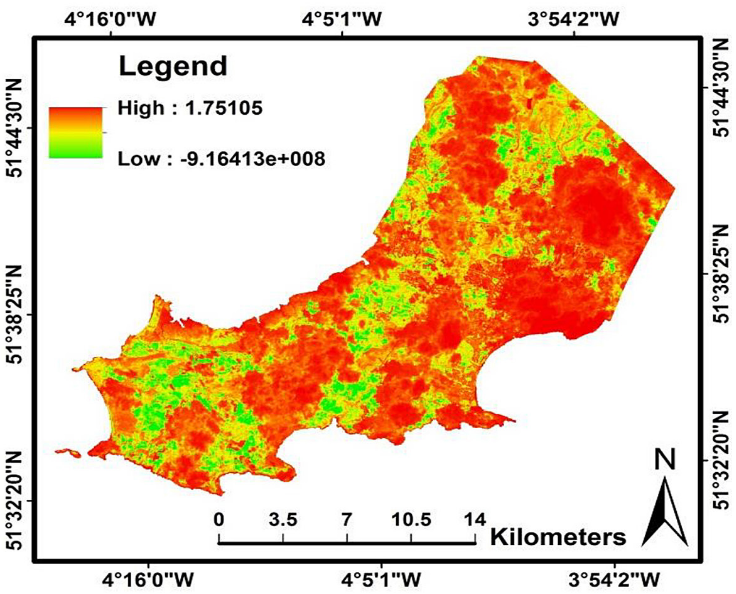


Figure 5. The detected values of CIG of Swansea



a) ETA



b) GEMI

Figure 6. The detected values for: (a) the extracted parameter ETA for Swansea, and (b) GEMI

monitoring index include: (1) holistic environmental assessment: GEMI provides a holistic approach to monitoring the environment, encompassing multiple indicators and parameters that collectively reflect the state of ecosystems. It enables the simultaneous assessment of various environmental factors, such as land cover changes, vegetation health, water quality, and atmospheric conditions; (2) early detection of environmental changes: by analyzing GEMI values over time, researchers can identify early signs of environmental changes, such as deforestation, urbanization, pollution, and climate-related shifts. This early detection is crucial for implementing timely conservation and mitigation measures; (3) biodiversity and habitat monitoring: GEMI aids in monitoring changes in habitats and biodiversity. It can reveal alterations in vegetation cover, which can impact various species' habitats and migration patterns; (4) climate change research: GEMI contributes to studies on climate change by tracking changes in vegetation cover and land use patterns. Such changes have implications for the Earth's energy balance, carbon cycle, and overall climate system. In general, and through the results obtained using the spatial and temporal analysis of the Landsat 8-OLI satellite image, we note that the values of chlorophyll levels reflected to the airspace are very large. Whereas, the global environmental monitoring index showed very high values for the rates of chlorophyll released to the atmosphere. Despite the environmental benefit that can be obtained from the provision of dense vegetation, as it reflects large levels of oxygen in the atmosphere and the absorption of carbon dioxide, this vegetation density clearly indicates the consumption of large quantities of water needed by the dense vegetation. As the high water consumption needed by the dense vegetation cover strongly affects the rates and quantities of fresh water available on the surface of the Earth, which is expected to strongly affect future water scarcity. Fresh water is used in all facilities of human life, and its shortage or scarcity will certainly affect its availability, especially since the world at the present time suffers from global warming, which generates high temperatures that increase evaporation rates, in addition to the high and unprecedented scarcity in low precipitation rates. Consequently, a prudent approach would involve managing water consumption by dense vegetation, utilizing groundwater, or scaling back vegetation cover to a level that doesn't compromise the availability of fresh water resources.

CONCLUSIONS

This study showcased the utilization of geographic information systems for environmental monitoring. Specifically, it highlighted the capabilities of Landsat 8-OLI in visualizing various vegetation indices. To assess sensitivity to different vegetation coverage scenarios, the CIG and GEMI were put to the test. This was achieved by analyzing a Landsat 8 image of Swansea county in Wales, UK, which contained comprehensive vegetation-related data. The resulting spectral VIs provided insights into the variations across vegetation conditions. By processing Landsat 8-OLI's Bands 3, 4, and 5 using GIS techniques, the CIG and GEMI were derived from RS data.

The research area exhibited pronounced vegetation characteristics as evidenced by the CIG and GEMI indices. The chlorophyll index spanned from -1 to 38, while the global environmental monitoring index ranged between 1.75105 and -9.61413e+008. Both indices effectively identified substantial vegetative land coverage. These extensive vegetated zones have the potential to influence the climate due to elevated chlorophyll emissions, thereby intensifying atmospheric impacts. Moreover, the substantial areas covered by vegetation will also contribute to heightened water demand, further impacting the water sector. Based on the findings, which highlighted substantial areas covered by vegetation, as evidenced by the CIG values and the GEMI environmental monitoring index, it is advisable to prioritize the utilization of GEMI due to its precise assessment of climate impacts caused by significant emissions. In regions prone to severe weather conditions, such as the United Kingdom and specifically Swansea County, employing various vegetation indices can serve as a valuable tool for estimating canopy health. To safeguard the water sector in Swansea from the repercussions of weather-related emissions reflected in land cover and land use, precautionary measures should be taken.

The proficiency of geographic information systems in interpreting cartographic data significantly aids in thematic mapping of global vegetation, offering visual insights into plant growth and well-being. The approach presented here holds potential for application in other studies with similar aims of environmental forest monitoring.

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